Psychology of Sport & Exercise 63 (2022) 102287

Contents lists available at ScienceDirect

Psychology of Sport & Exercise

journal homepage: www.elsevier.com/locate/psychsport

Physical effort biases the perceived pleasantness of neutral faces: A virtual reality study

Boris Cheval [a,b,*], Silvio Maltagliati [c], Layan Fessler [c], Ata Farajzadeh [d,e], Sarah N. Ben Abdallah [b], François Vogt [b], Margaux Dubessy [f], Maël Lacour [f], Matthew W. Miller [g,h], David Sander [a,b], Matthieu P. Boisgontier [d,e]

[a] Swiss Center for Affective Sciences, University of Geneva, Switzerland
[b] Laboratory for the Study of Emotion Elicitation and Expression (E3Lab), Department of Psychology, University of Geneva, Switzerland
[c] Univ. Grenoble Alpes, SENS, F-38000 Grenoble, France
[d] School of Rehabilitation Sciences, Faculty of Health Sciences, University of Ottawa, ON, Canada
[e] Bruyère Research Institute, Ottawa, ON, Canada
[f] Fondation Campus Biotech Genève, Geneva, Switzerland
[g] School of Kinesiology, Auburn University, USA
[h] Center for Neuroscience, Auburn University, USA

ARTICLE INFO

Keywords:
Exercise
Emotion
Automatic
Virtual reality
Physical exertion

ABSTRACT

The role of affective responses to effort in the regulation of physical activity behavior is widely accepted. Yet, to investigate these affective responses during physical activity, most studies used direct self-reported measures that are prone to biases (e.g., social desirability, ability to introspect). To reduce these biases, we used an indirect measure (i.e., an affect misattribution procedure) that assessed the implicit affective valence elicited by physical effort in 42 healthy young adults. Specifically, participants rated the pleasantness of neutral human faces presented in a virtual environment while cycling at different intensities. We used this rating as an indicator of implicit affective valence. Results showed that higher perceived effort was associated with lower pleasantness ratings of neutral faces, with this effect only emerging at moderate-to-high levels of perceived effort. Further analyses showed that higher actual effort was also associated with lower pleasantness ratings of neutral faces. Overall, these findings suggest that higher levels of perceived effort are associated with decreased affective valence during physical activity. Finally, this study presents a new indirect measure of affective valence during physical activity.

1. Introduction

Physical inactivity is a key health and societal problem. Over the past decades, tremendous efforts have been made to develop interventions tackling physical inactivity, but results have been disappointing – nowadays, insufficient physical activity is estimated to be responsible for one death every 6 s worldwide (World Health Organization, 2020). Tackling this inability to engage in physical activity is urgent to stand a chance of slowing the pandemic of physical inactivity (Boisgontier & Iversen, 2020; Kohl et al., 2012) and meet the targeted 15% reduction of physical inactivity by 2030 (World Health Organization, 2019). Recently, the essential role of affective mechanisms to explain physical inactivity has gained considerable attention (Brand & Ekkekakis, 2018; Cheval, Radel, et al., 2018; Conroy & Berry, 2017; Stevens et al., 2020; Williams & Evans, 2014). For example, experimental work has shown that experiencing positive affects during physical activity increases the likelihood of repeating this behavior in the future (Dunton, Leventhal, Rothman, & Intille, 2018; Kwan & Bryan, 2010; Liao, Chou, Huh, Leventhal, & Dunton, 2017; Magnan, Kwan, & Bryan, 2013; Rhodes & Kates, 2015; Schneider, Dunn, & Cooper, 2009; Williams & Bohlen, 2019; Williams, Dunsiger, Jennings, & Marcus, 2012). Moreover, although additional evidence is needed, affective mechanisms may moderate the intention–behavior associations (Rhodes, Cox, & Sayar, 2022; Williams, Rhodes, & Conner, 2019). In this study, we extended this line of research by investigating the implicit affective valence elicited by effort during physical activity using a newly-developed indirect

* Corresponding author. Campus, Biotech, Chemin des Mines 9, 1202 Genève, Switzerland.
E-mail address: boris.cheval@unige.ch (B. Cheval).

https://doi.org/10.1016/j.psychsport.2022.102287
Received 29 April 2022; Received in revised form 2 September 2022; Accepted 2 September 2022
Available online 7 September 2022

measure.

1.1. Affective evaluations of physical activity

Several theories suggest the affective evaluation of physical activity is an important factor in the regulation physical activity behavior (Brand & Ekkekakis, 2018; Cheval, Radel, et al., 2018; Conroy & Berry, 2017). Specifically, based on dual-process models that differentiate between reflective and automatic motivational processes regulating human behaviors, it has been argued that affective mechanisms can be evaluated at both the automatic and reflective levels. Automatic affective evaluations of physical activity (Conroy & Berry, 2017), also called automatic affective valuation (Brand & Ekkekakis, 2018) or automatic affective processing (Stevens et al., 2020), can be captured using eye-tracking or computerized reaction-time measures and include multiple indicators such as implicit attitudes (IAT; Greenwald et al., 1998), attentional bias (Pool, Brosch, Delplanque, & Sander, 2016) or approach-avoidance tendencies (Krieglmeyer & Deutsch, 2010). In contrast, reflective evaluations, also called reflective affect processing (Stevens et al., 2020), are typically captured using self-reported questionnaires and include cognitive projections (e.g., action plans) and affective evaluations (e.g., remembered affects, forecasted affects, or affective judgements).

These theories are supported by experimental studies showing that direct self-reported reflective evaluations of affects related to physical activity are predictive of physical activity (Rhodes, Fiala, & Conner, 2009; Williams & Bohlen, 2019). Moreover, studies showed that cues related to physical activity automatically capture attention (Berry, 2006; Berry, Spence, & Stolp, 2011; Calitri, Lowe, Eves, & Bennett, 2009; Cheval, Miller, et al., 2020), elicit positive automatic affective evaluations (Bluemke, Brand, Schweizer, & Kahlert, 2010; Chevance, Héraud, Varray, & Boiché, 2017; Conroy, Hyde, Doerksen, & Ribeiro, 2010; Rebar, Ram, & Conroy, 2015), and automatic behavioral approach tendencies (Cheval, Sarrazin, & Pelletier, 2014; Cheval, Sarrazin, Isoard-Gautheur, Radel, & Friese, 2015; Cheval, Tipura, et al., 2018), especially in the most physically active individuals (Cheval, Miller, et al., 2020). In turn, these affective evaluations are thought to influence physical activity engagement (Conroy & Berry, 2017). In sum, these findings suggest that reflective and automatic evaluations are critical in explaining engagement in physical activity, with individuals exhibiting more negative affective evaluations being at higher risk of physical inactivity.

However, the distinction between reflective and automatic processes is not trivial. Indeed, even performances in so-called “implicit” or “indirect” tasks have been found to be influenced by reflective processes (Corneille, Mierop, Stahl, & Hütter, 2019; Corneille & Hütter, 2020; Stahl, Haaf, & Corneille, 2016), questioning their validity to target purely automatic mechanisms. Therefore, considering that these processes vary in their degree of automaticity seems less problematic than an “all or nothing” approach. Accordingly, it seems more accurate to consider that the tasks used to measure implicit affective valence (e.g., reaction-time tasks) only reflected a more automatic and implicit measure than direct self-reported measures.

1.2. A learning process

At the conceptual level, automatic affective evaluations are thought to be gradually learned through the repetition of positive (e.g., pleasure) or negative (e.g., displeasure) affective responses felt during physical activity (Brand & Ekkekakis, 2018; Cheval & Boisgontier, 2021; Cheval, Radel, et al., 2018; Conroy & Berry, 2017). The repetition of positive affective responses during physical activity promotes the development of positive affective evaluations stored in memory, while the repetition of negative affective responses during physical activity favors the development of negative evaluations (Brand & Cheval, 2019). These automatic evaluations of the affects influence their controlled (also called reflective) evaluation that draw upon relevant propositional information, such as encoded affect and cognition (Brand & Ekkekakis, 2018). In sum, pleasant and unpleasant experiences influence the automatic and reflective evaluations of the affect related to physical activity.

1.3. Self-reported measures

Core affect, defined as *“the neurophysiological state that underlies simply feeling good or bad”* (Russell, 2009), is conceptualized in two dimensions: Valence and arousal (Russell, 1980). In exercise psychology, studies primarily focused on the valence of responses (i.e., pleasure vs. displeasure) and their associations with physical effort, an essential feature that is consubstantial of physical activity (Maltagliati, Sarrazin, Fessler, LeBreton, & Cheval, 2022). To investigate these associations, studies have mainly relied on direct self-reported measures, such as the Feeling Scale (Hardy & Rejeski, 1989) or the Empirical Valence Scale (Lishner, Cooter, & Zald, 2008). Results have consistently shown that affective valence and physical effort levels are strongly intertwined: Most individuals reported more negative affective valence (e.g., increased displeasure) when physical effort increased (Ekkekakis, Parfitt, & Petruzzello, 2011). These results are consistent with the theory of effort minimization in physical activity (TEMPA; Cheval & Boisgontier, 2021), which states that physical effort is, in most cases, perceived as an aversive experience that should be minimized or avoided.

1.4. The present study

This study is based on a new indirect measure of affective valence during exercise on a cycloergometer in a virtual environment. Participants were instructed to rate the pleasantness of human faces projected in a virtual environment while cycling at different effort intensities. The outcome of the rating was used as an indicator of the implicit affective valence during physical activity. Here, the term “implicit” is used because participants were not aware of what the outcome reflected (i.e., their affective valence state), which is consistent with the definition by De Houwer (De Houwer, 2006). Moreover, the rationale of our new paradigm is similar to that of the affect misattribution procedure (AMP; Payne, Cheng, Govorun, & Stewart, 2005; Payne & Lundberg, 2014), which is also defined as an implicit measure, because it is thought to capture the automatically activated responses based on the misattributions individuals make about the source of their affects or cognitions (Payne & Lundberg, 2014). However, the implicit nature of the AMP has recently been questioned (Hughes, Cummins, & Hussey, 2022).

In the AMP, primes (e.g., positively and negatively-valenced images) are briefly presented before neutral pictograms (e.g., Chinese pictographs) and participants are asked to judge the pleasantness of the pictograms. The affective valence automatically elicited by the prime are expected to impact participants’ responses, unknowingly. Specifically, positive and negative primes are expected to favor a positive or negative evaluation of the neutral pictograms, respectively. Our design is inspired by the AMP, with the conditions “positive and negative primes” being replaced by different levels of physical effort, and with the neutral pictographs being replaced by neutral faces. Based on previous literature (Cheval & Boisgontier, 2021; Ekkekakis et al., 2011), we hypothesized that higher levels of perceived effort would be associated with decreased valence of implicit affective responses, as measured by decreased pleasantness ratings of the neutral faces. Results supporting this hypothesis would suggest that changes in implicit affective valence as a function of perceived physical effort can be captured without relying on direct self-reported measures.

2. Method

Study preregistration can be found at https://aspredicted.org/JYD_GBF. Data, code, and other material can be found at https://doi.org/10.5281/zenodo.6405782.

2.1. Participants

The sample size required for 90% power was estimated using the simr package in R (Green & MacLeod, 2016), which was developed to calculate power for generalized linear mixed models based on Monte Carlo simulations. Details about this sample size estimate are available in the study's pre-registration (https://aspredicted.org/JYD_GBF). The results of the Monte Carlo simulation of the mixed model based on the predicted model (see Statistical Analysis) led to a minimum sample of N = 29 participants. We therefore planned to recruit at least 40 participants to account for data loss.

Recruitment was done through flyers distributed on the University of Geneva campus and in other places in Geneva. Participants interested in the study were asked to contact the research assistants by email or telephone. Participants did not receive any compensation for their participation in the study. In addition, they were also recruited via the University of Geneva's SONA participants recruitment system and were offered course credit for their participation. Participants fulfilling the following inclusion criteria were eligible for the study: 18 years of age or older, free of any medical conditions that would prohibit physical activity without supervision, and able to provide written informed consent. The exclusion criteria were an inability to follow the procedure, insufficient knowledge of French, or taking psychotropic medication or illicit drugs at the time of the study. A total of 57 participants were recruited, but data from 15 participants were removed from analyses because they did not complete the task due to problems with data collection (n = 6; 10.5%) or participants experiencing nausea during the virtual reality task (n = 9; 15.8%). The final sample was thus composed of 42 participants. The enrollment and data collection were completed before any analyses were conducted.

2.2. Apparatus

Cycling Task in an Immersive Virtual Reality Environment.

A whole-body virtual reality environment in which participants can exercise on a cycloergometer was developed using Unity technologies (Unity 3D 2021.2). A resistance, adapted for an indoor bike trainer (Tacx® Boost Bundle; Garmin), was added to the rear wheel of a static bike (Ortler Detroit) to experimentally manipulate physical effort (Fig. 1). The Tacx allows data to be sent at up to 2 hz, which is rather limited in the context of virtual reality. Accordingly, to stream the speed in the VR application, we used a motion capture system (Optitrack) that record and sends the rear wheel rotation data at 240 hz. This frequency is enough to ensure a good responsiveness of the system and to limit cybersickness. The virtual environment was delivered via a virtual-reality headset (HTC Vive Pro Eye). This headset has a resolution of 1440x1600 pixels per eye, a refresh rate of 90Hz, and a field of view of 110°. The lighthouse-based HMD tracking was replaced with an OptiTrack optical motion capture system (Prime 13 camera, 240 fps frame rate) used to acquire bike wheel speed and handlebar orientation. A pilot study was conducted (n = 5) to test the feasibility of the task. Specifically, the different levels of effort (i.e., the wattage of the resistance), task duration, method and time interval for evaluating the faces, as well as instruction comprehension were conducted during this pilot phase. All task characteristics were predetermined based on our engineers' previous experience with this specific device. The pilot study confirmed that the chosen configuration was well suited for our study. To increase ecological validity, we used different types of ground (e.g., floor, grass). A video of the cycling task is available at https://doi.org/10.5281/zenodo.6405782.

2.3. Stimuli

The FACSGen facial action coding system (Krumhuber, Tamarit, Roesch, & Scherer, 2012) was used to create realistic 3D facial expressions on avatar faces. Studies showed that the FACSGen tool generates experimentally manipulated synthetic avatar emotions that are easily identifiable by naïve observers (Mumenthaler & Sander, 2012, 2015; Scherer, Mortillaro, Rotondi, Sergi, & Trznadel, 2018). We used a sample of 70 validated faces[1] (35 males and 35 females) from the Geneva Faces And Voices database (GEFAV; Ferdenzi et al., 2015). These 70 faces displayed a negative (i.e., anger), positive (happiness), or neutral expression, for a total of 210 stimuli.

2.4. Procedure

Participants completed a 1-h session that started with written informed consent to participate in the study approved by the Ethics Committee of Geneva Canton, Switzerland (CCER-2019-00065). Next, participants completed a questionnaire assessing demographics and potential confounding variables (i.e., thirst, hunger, recent physical activity, sleep pattern, caffeine, alcohol, and cigarette consumption, potential health problems, visual acuity, desire for exercise and rest, usual physical activity, motivation to be physically active, and exercise addiction). Then, participants sat on the bike and a virtual reality headset was positioned on their head by the experimenter under the supervision of a virtual reality engineer. Participants familiarized themselves with the virtual environment by pedaling at a self-selected speed for 30s. Next, the participants were asked to rate the pleasantness of the faces while cycling at different levels of physical effort. After the cycling task, a questionnaire was used to assess prior cycling and virtual reality experience, as well as the specific virtual reality experience of the current study (i.e., fatigue, boredom, comfort, ease, agreeability, nausea, and perceived immersion) using the Immersive Experience Questionnaire (IEQ; Jennett et al., 2008).

2.5. Measures

Perceived Pleasantness of Faces.

Participants performed a modified version of the AMP to assess implicit affective valence elicited during a physically active performance. Participants were asked to rate the pleasantness of the faces displayed on the virtual environment while cycling at five intensities: very easy (115.5 W), easy (178.5 W), moderate (241.5 W), hard (304.5 W), very hard (367.5 W). Each level of physical effort was repeated six times. In total, participants completed two 15-min blocks of 1-min cycling bouts, with a 5-min break between blocks, for a total duration of approximately 35 min (Fig. 1). The first 16 s of each 1-min bout was an adaptation phase in which the participants became accustomed to the new level of effort required, while maintaining the same frequency of pedaling. During the last 44 s, participants used the left and right handlebar buttons to rate 7 different faces on a Likert scale titled *"evaluation of the face" ("evaluation du visage"* in French) ranging from 1 "negative" to 9 "positive" that appeared below the face. The faces were presented for a duration of 2 s with a 2-s delay between the pleasantness evaluation of the face and the presentation of the next face. There was no response time limit for the evaluation of each face, but participants were required to evaluate the seven faces in 44 s as the pilot study suggested that it was sufficient to rate all seven faces. No participants took more than 44 s to evaluate the seven faces.

Overall, participants had to evaluate 21 different faces that were presented twice during each of the five levels of physical effort, totaling 210 trials. For each participant, the 21 faces (7 neutral, 7 negatives, 7 positives) were randomly selected from the 210 FACSGen faces. The faces were randomized across the two blocks, but each emotional

[1] The faces from the GEFAV database were: 104, 106, 107, 109, 116–118, 123, 124, 131, 132, 147, 154, 160, 169, 177, 183, 190, 198, 204, 207, 244, 261, 280, 293, 302, 305, 306, 312, 313, 316, 323, 325, 329, 330, 336, 339, 344, 345, 346, 364, 366, 372, 373, 382, 387–389, 392, 395, 397, 398, 401, 405, 408–410, 413, 418, 422–425, 427, 437, 438, 440, 448, 450.

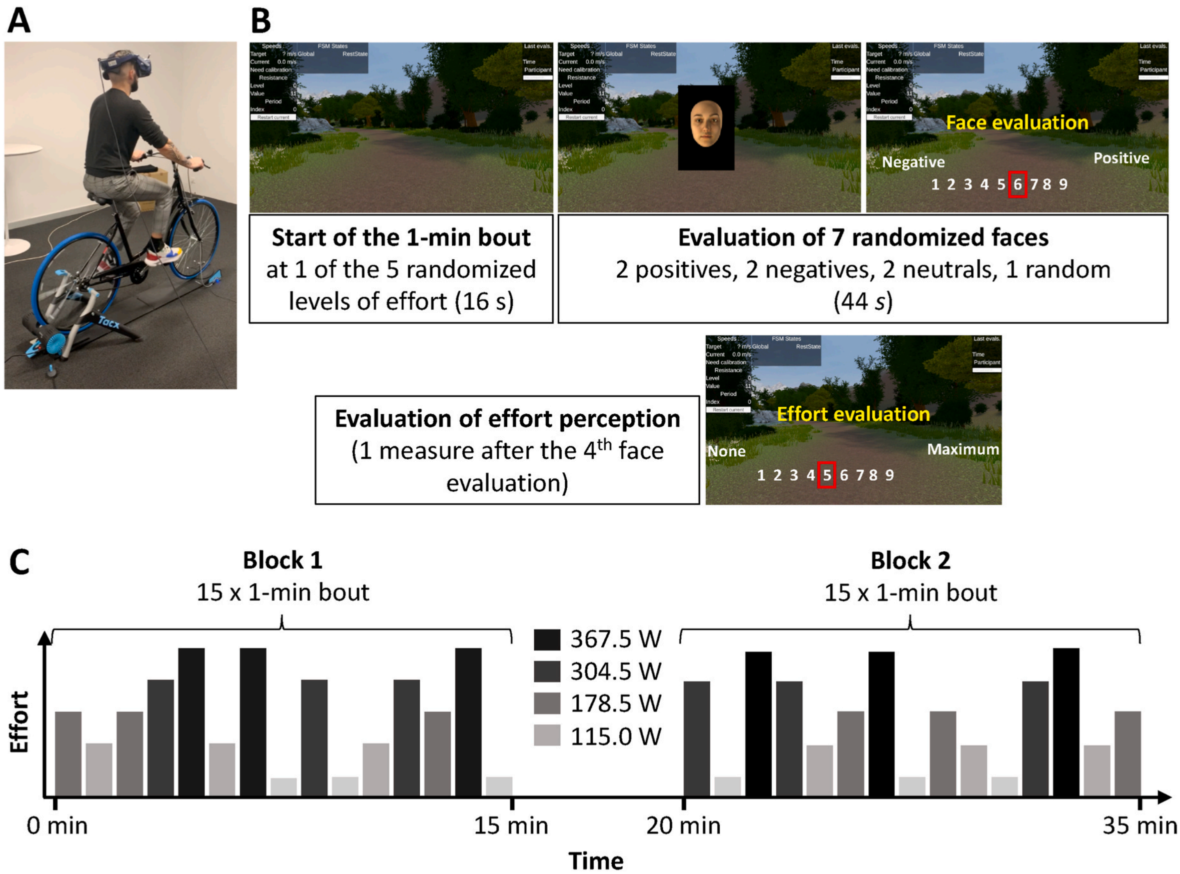

Fig. 1. Evaluative task and procedure.
Note. A. evaluative task. Participants were instructed to rate the pleasantness of faces displayed in the virtual environment while cycling at different intensities. *B. Procedure.* Participants were asked to complete 15 x 1-min cycling bouts at different effort intensity. *C. Randomization within-participants.* The order of the effort intensity and of the projection of the faces were randomized for each participant. The total duration of the task was ~35-min, split into two blocks.

valence was presented at least twice in each 1-min bout (i.e., 2 neutral, 2 positive, 2 negative, and 1 additional face that was randomly selected from the 210 faces). The order of the different levels of the thirty 1-min cycling bouts was randomized for each participant. This strategy allowed us to avoid the potential confounding influence of fatigue on the results. The perceived pleasantness of the neutral faces was used as the primary outcome. The negative and positive faces were added for two main reasons: To make the task more engaging and to keep participants from guessing the purpose of the study.

2.6. Perceived effort

Perceived effort was assessed after the fourth face was evaluated using a Likert scale titled *"perceived effort"* (*"effort ressenti"* in French) ranging from 1 "none" to 9 "maximum". Perceived effort was used as the main predictor in the statistical analyses. Additional analyses were conducted to examine the effect of actual effort.

2.7. Covariates

The following covariates were included in the model: block (1 vs. 2), bout (1–15), age, body mass index, and sex.

2.8. Statistical Analysis

Participants' actions and responses were recorded using the underlying C# language and the Unity application. Data included participant's identification code, block index (1, 2), bout index (1–15), trial index within bout (1–6), actual effort (1–5), perceived effort (1–9), the code of the face (see footnote 1), the gender of the avatar's face (woman, man), the valence of the avatar's face (neutral, positive, negative), and the rating of the pleasantness of the avatar's face (1–9).

Implicit affective valence during cycling was assessed using the pleasantness ratings of the neutral faces and were analyzed using linear mixed models. Mixed models allow for correct parameter estimation when data contains multiple cross-random effects, as in the current study where participants are crossed with stimuli (i.e., faces). In these conditions, mixed models have been found to decrease the risk of type-I error compared to traditional ANOVA (Boisgontier & Cheval, 2016). The linear mixed models included linear and quadratic effects of perceived effort as fixed factors. The quadratic effect was included to account for potential non-linear effects of perceived effort on the evaluation of neutral faces. A significant quadratic effect would indicate that the effect of perceived effort on implicit affective valence was not constant across the perceived effort range (i.e., 1 to 9). For example, as observed for direct self-reported affective valence, the negative association between perceived effort and affective valence may only appear when effort intensity reaches a threshold (Ekkekakis et al., 2011). If the quadratic effect of perceived effort was significant, simple slopes, region of significance, and confidence bands were examined using computational tools for probing interactions in mixed models (Preacher, Curran, & Bauer, 2006). Models were adjusted for the above-mentioned covariates (i.e., block, bout, age, body mass index, sex). All these variables were centered to allow for correct interpretation of the model intercept. Participants and stimuli (i.e., faces) were specified as random factors and included a random slope for the perceived effort at the level of participants. This random effect allowed the effect of perceived effort on pleasantness to vary across participants.

To reduce convergence issues, each model was optimized using the default BOBYQA optimizer (Powell, 2009), the Nelder-Mead optimizer (Nelder & Mead, 1965), the nlimb optimizer from the optimx package (Nash & Varadhan, 2011), and the L-BFGS-B optimizer (see Cheval, Bacelar, et al., 2020; Cheval et al., 2021; Frossard & Renaud, 2019, for similar procedure). Estimates of the effect size were reported using the conditional and marginal pseudo R^2 from the MuMin package (Barton, 2018). *P* values for the global effect of perceived effort were provided using likelihood ratio tests, in which we compared models with and without perceived effort as a fixed or random factor. Statistical assumptions associated with linear mixed models (i.e., normality of the residuals, linearity, multicollinearity, and undue influence) were met. The analyses were conducted in R with the lme4 and lmerTest packages (Bates, Mächler, Bolker, & Walker, 2014; Kuznetsova, Brockhoff, & Christensen, 2015; R Core Team, 2017).

3. Secondary analyses

Two additional analyses were conducted. First, perceived effort was replaced by actual effort level (i.e., the five conditions of physical effort) as the main predictor. Second, we tested whether the usual level of moderate-to-vigorous physical activity affected perceived pleasantness and whether it moderated the pattern of association between perceived effort and perceived pleasantness.

3.1. Sensitivity analysis

In a sensitivity analysis, participants who felt nauseous during the task under virtual reality (i.e., > 5 on a scale ranging from 1 “no nausea at all” to 7 “a lot of nausea”), but who still completed the experimental procedure, were excluded because nausea can have a confounding influence on the implicit affective rating of the faces.

4. Results

4.1. Descriptive results

Table 1 shows the characteristics of the participants. The final sample included 42 participants (29 females; age = 27.2 ± 9.3 years; body mass index = 22.45 ± 3.45 kg m^{-2}). On average, neutral, positive, and negative faces were respectively rated 4.87 (±0.50), 6.55 (±0.61), and 2.89 (±0.62) out of nine, $F_{(2, 82)} = 429.51$, $p < .001$, $\eta^2 = 0.87$. These ratings confirm that participants were able to accurately determine the expression of the avatars’ faces. Moreover, the perceived effort increased when exercise intensity increased. Specifically, perceived effort was rated at 3.92 (±1.64), 4.71 (±1.43), 5.53 (±1.36), 5.87 (±1.43), 6.32 (±1.41) out of nine for the very easy (115.5 W), easy (178.5 W), moderate (241.5 W), hard (304.5 W), very hard (367.5 W) condition, respectively, $F_{(4, 64)} = 47.08$, $p < .001$, $\eta^2 = 0.26$. This result confirms that the study design was effective in changing the perception of effort during the task.

Table 1
Descriptive statistics.

N = 42	Mean	SD
Age (years)	27.2	9.3
Sex (number; %)		
Females	29	69%
Males	13	31%
Body Mass Index	22.45	3.45
Usual physical activity (min per week)	152.3	151.2
Evaluation of the pleasantness of faces (Likert scale; 1–9)		
Negative (anger) faces	2.89	0.62
Neutral faces	4.87	0.50
Positive (happiness) faces	6.55	0.61
Perceived effort (Likert scale; 1–9)		
Averaged over the exercise task	5.27	1.21
By actual levels of effort		
Very easy (115 W)	3.92	1.64
Easy (178.5 W)	4.71	1.43
Medium (241.5 W	5.53	1.36
Hard (304.5 W)	5.87	1.43
Very hard (367.5 W)	6.32	1.41

Nots. SD = standard deviation; W = watts. Body mass index and usual level of moderate-to-vigorous physical activity were self-reported.

5. Main results: perceived effort and pleasantness of neutral faces

Perceived effort was associated with the perceived pleasantness of neutral faces (*p* for global effect = 0.005; Fig. 2A). Both the linear (b = −0.027, 95% confidence interval [CI] = −0.048 to −0.005, *p* = .020) and quadratic effect (b = −0.009, 95% CI = −0.017 to −0.001, *p* = .022) of perceived effort on pleasantness of neutral faces were significant (Table 2). The region of significance of the simple slope revealed that the negative effect of perceived effort on pleasantness of neutral faces had its lower bound estimated at 4.5 on the scale of effort ranging from 1 to 9 (Fig. 2B). Since the scale had a one-unit interval, this result suggested that an increase in perceived effort was not significantly associated with a change in pleasantness of neutral faces when the level of perceived effort was <5. However, this association was significantly negative when the level of perceived effort was ≥5. For example, when perceived effort was low (e.g., equal to 2), an increase in perceived effort was not significantly associated with a change in pleasantness of neutral faces (b = 0.024, 95% CI = −0.025 to 0.076, *p* = .332). Conversely, when perceived effort was high (e.g., equal to 8), an increase in perceived effort was associated with a decreased pleasantness of neutral faces (b = −0.089, 95% CI = −0.144 to −0.033, *p* = .002). The other effects were not significant, although female participants tended to evaluate neutral faces less positively than male participants (b = −0.322, 95% CI = −0.658 to −0.014, *p* = .068). The variables included in the model explained 3.1% (fixed effects) and 38.8% (fixed + random effects) of the variance in pleasantness of neutral faces.

6. Secondary results

Actual Physical Effort.

Results showed that an increase in actual effort (exercise intensity) was associated with a decrease in pleasantness of neutral faces (b = −0.020, 95% CI = −0.048 to −0.005, *p* = .049) (Table S1, Figure S1). The quadratic effect was not significant (b = 0.002, 95% CI = −0.015 to 0.019, *p* = .808), suggesting that the magnitude of the effect of actual effort on pleasantness of neutral faces was similar across the 5 levels of actual effort. Overall, results were consistent with those observed for perceived effort (main results): Higher exercise intensities were associated with lower ratings of neutral faces.

6.1. Moderate-to-vigorous physical activity

Results showed no evidence of a direct effect of the usual level of moderate-to-vigorous physical activity on perceived pleasantness (b = 5.4E-04, 95% CI = −4.5E-04 to 1.5E-03, *p* = .294) or a moderating effect on the linear (b = −4.0E-06, 95% CI = −1.5E-04 to 1.5E-03, *p* = .958) and quadratic effect of perceived effort (b = 1.3E-05, 95% CI = −4.9E-05 to 7.5E-05, *p* = .673). Both the linear and quadratic effect of perceived effort on pleasantness of neutral faces remained unchanged relative to the main analysis (Table S2).

6.2. Sensitivity results

Results of the sensitivity analysis excluding participants who had nausea during the experiment (N = 6) were consistent with the results of the main analysis (Table S3, Figure S3).

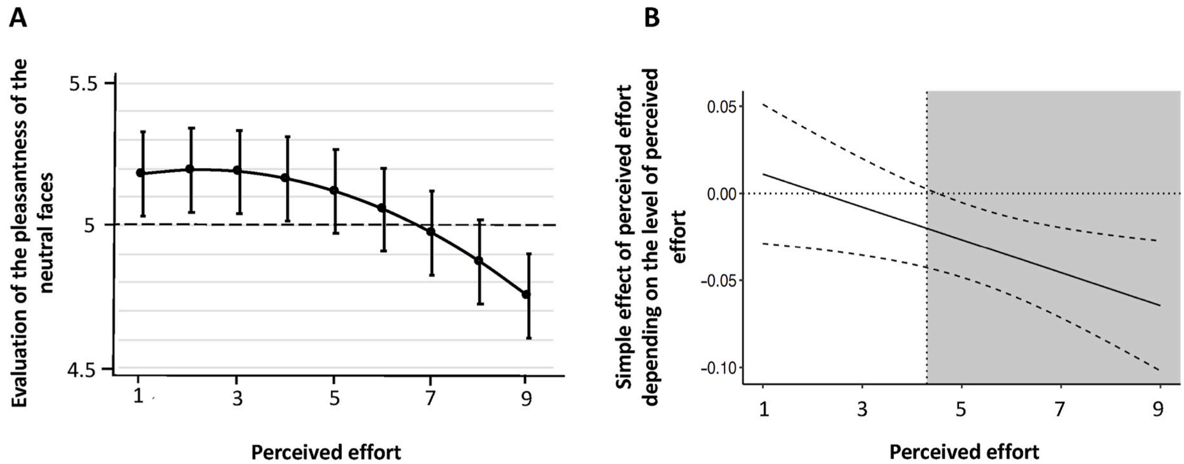

Fig. 2. Evaluation of the pleasantness of the neutral faces as a function of perceived effort
Notes. Results of the linear mixed models. A. Prediction of the pleasantness of neutral faces as a function of perceived effort. Errors bars = standard errors. Dashed line = neutral evaluation of the neutral face (i.e., 5 on the scale ranging from 1 to 9). Above the dashed line, pleasantness is positively biased. Below the dashed line, pleasantness is negatively biased. *B. Region of significance of the effect of perceived effort on pleasantness of neutral faces as a function of the level of perceived effort.* A negative effect indicates that an increase in perceived effort was associated with a decreased rating of the neutral faces; solid line = mean; dashed line = 95% confidence interval; grey area = region of significance ($p < .005$).

Table 2
Results of the mixed models predicting the evaluation of the pleasantness of neutral faces as a function of the perceived level of effort.

Pleasantness of the neutral faces		
N = 42	b (95CI)	*p*
Fixed Effects		
Intercept	5.118 (4.832–5.405)	<.001
Perceived effort		
Linear effect	−0.027 (−0.048–−0.005)	.020
Quadratic effect	−0.009 (−0.017–−0.001)	.022
Covariates		
Age	−0.003 (−0.020–0.014)	.723
Sex (ref. males)		
Females	−0.322 (−0.658–0.014)	.068
Body mass index	−0.029 (−0.012–0.070)	.177
Block (ref. Block 1)		
Block 2	−0.032 (−0.027–0.091)	.284
Bout (1–15)	0.005 (−0.002–0.012)	.149
Random Effects		
Participants		
Intercept	0.213	
Perceived effort	<0.001	
Corr. (Intercept, Perceived effort)	−0.38	
Stimuli (Faces)		
Intercept	0.112	
Residual	0.590	
R^2	Marginal = .034; Conditional = .378	

Note. 95CI = confidence intervals at 95%.

7. Discussion

7.1. Main findings

In the current study, participants performed a cycling task under virtual reality while rating the pleasantness of neutral faces displayed in the virtual environment (i.e., an indirect measure) to capture implicit affective valence during physical activity. Consistent with our hypothesis, we found that higher perceived effort was associated with lower perceived pleasantness of neutral faces, with this effect only emerging at moderate-to-high levels of perceived effort. Hence, our findings suggest that indirect measures can be used to capture implicit affective valence during a physically active performance.

7.2. Comparison with other studies

Our results showing that the implicit positive affective valence only decreased at moderate-to-high perceived physical effort supports previous literature (Ekkekakis et al., 2011). Previous research indeed showed that as exercise intensity increases and exceeds the ventilatory threshold, most individuals report decreased pleasure and increased displeasure (Ekkekakis et al., 2011). This affective response could be explained by interoceptive feedback resulting from the increased effort including, but not limited to, the release of adrenaline and growth hormone, and the accumulation of inorganic phosphate interfering with muscle function (Allen & Westerblad, 2001; Deijen, Arwert, Witlox, & Drent, 2005; Kindermann et al., 1982). Likewise, neuroscientific studies have shown that effort is generally processed as a cost, i.e., an aversive experience to be avoided whenever possible (Hagura, Haggard, & Diedrichsen, 2017; Prévost, Pessiglione, Météreau, Cléry-Melin, & Dreher, 2010). Thus, the current study further strengthens the well-validated relationship between effort and affective valence by extending this relationship to indirect measures of affective valence.

However, we found no statistical evidence of improved positive affective valence when exercise intensity increased at lower levels of perceived effort. This result contrasts with previous studies that observed an improvement in direct self-reported affective valence at low effort intensities (Ekkekakis et al., 2011). This discrepancy could be explained by differences in the methods of measuring affective valence. In particular, it has been argued that cognitive factors are dominant in shaping affective responses at low effort intensities, while interoceptive cues gain salience when exercise intensity approaches functional limits (Ekkekakis, 2003). This rationale suggests that the positive affective valence reported during low-intensity exercise reflects conscious deliberation about one's own affective response rather than the true (i.e., not cognitively mediated) affective response *per se*. Further, this cognitive reflection about one's own affective state can be biased by normative responses, social pressure, and desirability (Ekkekakis et al., 2018). Accordingly, the self-reported increase in positive affective state when individuals move from rest to low effort intensity could reflect a true increase but could also reflect a self-reported bias. This discrepancy may also be explained by the fact that our task could not discriminate affective valence with the same granularity as direct self-reported measures for at least two reasons. First, to measure pleasantness, we used a Likert scale ranging from one to nine with one-point increments, which prevented the capture of small changes in affective responses. Using another type of scale, such as a visual analog scale, could offer greater precision. Second, we did not measure the affective valence at rest, which reduced our range of low-intensity effort. In the absence of a rest condition, we cannot draw strong conclusions from the results observed at low levels of effort.

Our results investigating the effect of actual effort on implicit affective valence during physical activity were consistent with the main analysis, revealing that higher exercise intensities were associated with less positive implicit affective valence. However, contrary to the effect of perceived effort, this effect was linear, suggesting a detrimental impact of actual effort on the affective valence even when effort was lower (e.g., from a "very easy" to an "easy" bout). This result contrasts with previous studies based on self-reported measures showing that the negative effect of effort intensity on the affective valence only emerged at high effort levels (Ekkekakis et al., 2011). Yet, as mentioned above, this difference could be explained by a lack of granularity of our metric compared with the self-reported measures used in prior studies. Most importantly, we did not adjust the actual level of effort for cardiorespiratory fitness. Accordingly, a given level of physical effort (e.g., 241.5 W) may be associated with low effort in some participants, but with high effort in others. This large amount of inter-individual variability may have distorted the observed associations.

Finally, to the best of our knowledge, only one study has sought to capture affective valence during exercise without relying on a direct self-reported measure (Timme & Brand, 2020). This study investigated the facial actions (e.g., mouth open, nose wrinkle) during an incremental physical exercise as indicators of the affective valence. Results showed a quadratic decline in direct self-reported affective valence as exercise intensity increased and observed that nose wrinkle correlated with this negative response. Although the measures (i.e., facial action vs. an indirect measure of affective valence) and methods used (i.e., incremental exercise vs. random bouts of exercise intensity) differed between the studies, results were consistent and support the feasibility of capturing affective valence during physical activity without relying on the direct self-reported affective responses.

At the conceptual level, our findings are in line with previous literature arguing that high-intensity activities are, despite inter-individual differences (Ekkekakis, Hall, & Petruzzello, 2005), associated with a decreased pleasure. Indeed, engaging in high-intensity physical activity may elicit a negative affective response, which in turn, through the repetition of these negative experiences, becomes encoded in an individual's evaluative and associative system of memory. In turn, these negative affective evaluations can decrease engagement in physical activity. Consistent with this idea, recent theories contend that affective mechanisms play a pivotal role in explaining the gap between intention and action (Brand & Ekkekakis, 2018; Cheval, Radel, et al., 2018; Conroy & Berry, 2017). For example, studies showed that affective responses during physical effort predict future engagement in physical activity (Rhodes, McEwan, & Rebar, 2019; Williams & Bohlen, 2019; Williams et al., 2012). Particularly, TEMPA argues that affective experiences and perceived effort are strongly intertwined – increased perceived effort is associated with less positive affective responses (Cheval & Boisgontier, 2021; Cheval, Radel, et al., 2018). According to this theoretical model, positive affective experiences toward physical activity are thought to help individuals to overcome human's innate attraction toward physical effort minimization (Cheval, Bacelar, et al., 2020; Cheval & Boisgontier, 2021; Cheval, Sarrazin, Boisgontier, & Radel, 2017; Klein-Flügge, Kennerley, Friston, & Bestmann, 2016; Prévost et al., 2010).

In our study, exercise intensity was manipulated to ensure high within-subject variance in perceived effort, allowing us to assess the links between perceived effort and affective responses. We were not interested in predicting between-participants differences in affective responses during physical activity or in testing how these differences could predict future physical activity participation. However, future studies should use our indirect measure of affective valence in combination with questionnaires (i.e., to assess cognitive and motivational constructs related to physical activity) to investigate whether and how indirect affective valence elicited during physical activity are related to subsequent and accelerometer-measured physical activity.

7.3. Strengths and limitations

We believe that this study has several strengths. First, we relied on a pre-registered and highly-powered study, which are considered good research practices (Boisgontier, 2022). Second, we applied an analytical approach well-suited to examine data with cross-random factors (i.e., participants and faces). Third, we have built a design allowing the randomization and repetition of different levels of effort across time, while previous literature mainly relied on incremental exercise. Therefore, contrary to previous literature, our method accounts for a potential confounding effect of fatigue. Fourth, we developed an innovative whole-body exercise task under virtual reality combined with a task that indirectly measures affective valence at various levels of effort. Virtual reality allowed us to build knowledge based on an experimental task conducted in a well-controlled setting, while maintaining ecological validity.

However, this study also has limitations. First, we did not include a direct self-reported measure of affective valence. Although adding such measures could have had a confounding effect on the affective evaluations of the neutral faces (i.e., by asking the participants to focus on their affective states), this would have allowed the comparison of a direct self-reported and an indirect measure of affective valence during physical activity. Moreover, assuming responses are genuinely reported, self-reported measures are currently the standard method for measuring affective response (Williams, Rhodes, & Conner, 2018). Accordingly, adding a direct self-reported measure would have allowed us to better assess the criterion validity of our indirect measure. However, it should be noted that, from a dual-model perspective, some affective responses would be less accessible to consciousness than others, preventing direct self-report measurement from accurately capturing them. This possibility reinforces the need for multiple methods to measure affective response during physical activity. Second, we developed and used a task inspired from the AMP. Accordingly, we assumed (1) that the prime (i.e., the different levels of effort) elicited a valenced affective response and (2) that this affective response incidentally influenced the evaluation of the neutral faces (3) because the affective state were irrelevant to the decision at hand (i.e., this state does not provide a useful information for evaluating the target). However, we did not empirically verify the extent to which participants were indeed unaware of the fact that the measured outcome aimed to reflect their affective valence state, although this procedure is warranted before a measure can be called implicit (De Houwer, 2006). Likewise, it has been recently shown that participants' awareness of the primes strongly moderates the effects observed in the AMP (Hughes et al., 2022), thereby questioning the implicit nature of this task. Yet, we can still consider that our measure of affective valence to physical activity is less dependent on participants' introspective ability and is less susceptible to social desirability biases than direct self-reported measures. Third, we relied on a Likert scale ranging from one to nine with one-point increments to measure affective valence and perceived effort. Although these scales were selected after the pilot study and have proven to be particularly easy to use in combination with the mode of response (i.e., pressing the handlebar buttons), a visual analog scale could more accurately track how the affective responses change across the whole range of perceived effort. Fourth, the possibility of a *contagion effect* between blocks cannot be ruled out despite the randomization of the level of effort. A bout could be associated with more positive affective valence if the previous bout was perceived as pleasant, with a low effort (e.g., switching from a very easy effort to a moderate effort). Alternatively, there could be a *contrast effect*: a bout could be associated with more positive affective valence because the preceding bout was unpleasant and very intense (e.g., switching from a very hard effort to an easier effort). Fifth, although our study focused on perceived effort rather than on actual effort, as the former is expected to be the most critical in explaining affective responses according to TEMPA (Cheval & Boisgontier, 2021), the absence of standardization of the actual effort intensity between participants is a limitation. For example, it would have been possible to examine and compare the association of an objective indicator of effort intensity (e.g., oxygen uptake; VO_2) and perceived effort with affective responses. A standardized effort manipulation approach is thus warranted in future studies. Sixth, our sample consisted of healthy young adults. Although it was important to examine how affective responses varied with effort level in this population, additional studies are needed to examine whether these responses differ in clinical populations, such as individuals suffering from chronic conditions, who are typically less physically active than the general population. Seventh, although the order of appearance of the faces was random, we cannot rule out the possibility that the positive and negative faces may have primed the rating of neutral faces. Future studies using only neutral stimuli are needed. Finally, we observed an important dropout rate because of virtual reality sickness (i.e., 15.8%), which is yet consistent with the literature (i.e., 15.6%) (Saredakis et al., 2020).

8. Conclusion

Beyond a certain level of effort, perceived as light by participants, an increase in perceived effort was associated with a decrease perceived pleasantness of neutral faces. This finding supports previous results based on direct self-reports showing that higher intensities of physical activity are associated with decreased affective valence, and extent them to an indirect measure that are thought to assess more automatic and implicit affective valence. This study paves the way for the development and use of such indirect measures of affective valence in field-based applied research on physical activity behavior.

Author contribution statement

BC; designed the study. SNB and FV collected the data. BC analyzed the data. MD and ML supervised the data collection. BC, SM, MPB drafted the manuscript. MPB supervised the study. All authors critically appraised and approved the final version of the manuscript.

Declarations

Funding. B.C. is supported by an Ambizione grant (PZ00P1_180040) from the Swiss National Science Foundation (SNSF). M.P.B. is supported by the Natural Sciences and Engineering Research Council of Canada (RGPIN-2021-03153) and by the Banting Research Foundation.

Ethical approval

This study was approved by the Ethics Committee of Geneva Canton, Switzerland (CCER-2019-00065).

Consent to participate

All the participants agreed to participate and signed a written informed consent.

Consent for publication

All the authors have agreed to the by-line order and to the submission of the manuscript in this form.

Availability of data and material

The dataset is available at https://doi.org/10.5281/zenodo.6405782

Code availability

The code is available at https://doi.org/10.5281/zenodo.6405782.

Data availability

Data shared on Zenodo, as well as scoot.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.psychsport.2022.102287.

References

Allen, D., & Westerblad, H. (2001). Role of phosphate and calcium stores in muscle fatigue. *The Journal of Physiology, 536*(3), 657–665. https://doi.org/10.1111/j.1469-7793.2001.t01-1-00657.x

Barton, K. (2018). MuMIn: Multi-model inference. *R package version 1.42.1.* https://CRAN.R-project.org/package=MuMIn.

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2014). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software, 67*(1), 1–48. https://doi.org/10.18637/jss.v067.i01

Berry, T. R. (2006). Who's even interested in the exercise message? Attentional bias for exercise and sedentary-lifestyle related words. *Journal of Sport & Exercise Psychology, 28*(1), 4–17. https://doi.org/10.1123/jsep.28.1.4

Berry, T. R., Spence, J. C., & Stolp, S. M. (2011). Attentional bias for exercise-related images. *Research Quarterly for Exercise & Sport, 82*(2), 302–309. https://doi.org/10.1080/02701367.2011.10599758

Bluemke, M., Brand, R., Schweizer, G., & Kahlert, D. (2010). Exercise might be good for me, but I don't feel good about it: Do automatic associations predict exercise behavior? *Journal of Sport & Exercise Psychology, 32*(2), 137–153. https://doi.org/10.1123/jsep.32.2.137

Boisgontier, M. P. (2022). Research integrity requires to be aware of good and questionable research practices. *European Rehabilitation Journal, 2*(1), 1–3. https://doi.org/10.52057/erj.v2i1.24

Boisgontier, M. P., & Cheval, B. (2016). The anova to mixed model transition. *Neuroscience & Biobehavioral Reviews, 68*, 1004–1005. https://doi.org/10.1016/j.neubiorev.2016.05.034

Boisgontier, M. P., & Iversen, M. D. (2020). Physical inactivity: A behavioral disorder in the physical therapist's scope of practice. *Physical Therapy, 100*(5), 743–746. https://doi.org/10.1093/ptj/pzaa011

Brand, R., & Cheval, B. (2019). Theories to explain exercise motivation and physical inactivity: Ways of expanding our current theoretical perspective. *Frontiers in Psychology, 10*, 1147. https://doi.org/10.3389/fpsyg.2019.01147

Brand, R., & Ekkekakis, P. (2018). Affective–Reflective Theory of physical inactivity and exercise. *German Journal of Exercise and Sport Research, 48*(1), 48–58. https://doi.org/10.1007/s12662-017-0477-9

Calitri, R., Lowe, R., Eves, F. F., & Bennett, P. (2009). Associations between visual attention, implicit and explicit attitude and behaviour for physical activity. *Psychology and Health, 24*(9), 1105–1123. https://doi.org/10.1080/08870440802245306

Cheval, B., Bacelar, M., Daou, M., Cabral, A., Parma, J., Forestier, C., … Miller, M. W. (2020). Higher inhibitory control is required to escape the innate attraction to effort minimization. *Psychology of Sport and Exercise, 51*, Article 101781. https://doi.org/10.1016/j.psychsport.2020.101781

Cheval, B., & Boisgontier, M. P. (2021). The theory of effort minimization in physical activity. *Exercise and Sport Sciences Reviews, 49*(3), 168–178. https://doi.org/10.1249/JES.0000000000000252

Cheval, B., Cabral, D. A. R., Daou, M., Bacelar, M., Parma, J. O., Forestier, C., … Boisgontier, M. P. (2021). Inhibitory control elicited by physical activity and inactivity stimuli: An EEG study. *Motivation Science, 7*(4), 386–389. https://doi.org/10.1037/mot0000236

Cheval, B., Miller, M. W., Orsholits, D., Berry, T., Sander, D., & Boisgontier, M. P. (2020). Physically active individuals look for more: An eye-tracking study of attentional bias. *Psychophysiology, 57*(6), Article e13582. https://doi.org/10.1111/psyp.13582

Cheval, B., Radel, R., Neva, J. L., Boyd, L. A., Swinnen, S. P., Sander, D., & Boisgontier, M. P. (2018). Behavioral and neural evidence of the rewarding value of exercise behaviors: A systematic review. *Sports Medicine, 48*(6), 1389–1404. https://doi.org/10.1007/s40279-018-0898-0

Cheval, B., Sarrazin, P., Boisgontier, M. P., & Radel, R. (2017). Temptations toward behaviors minimizing energetic costs (BMEC) automatically activate physical activity goals in successful exercisers. *Psychology of Sport and Exercise, 30*, 110–117. https://doi.org/10.1016/j.psychsport.2017.02.006

Cheval, B., Sarrazin, P., Isoard-Gautheur, S., Radel, R., & Friese, M. (2015). Reflective and impulsive processes explain (in)effectiveness of messages promoting physical activity: A randomized controlled trial. *Health Psychology, 34*(1), 10–19. https://doi.org/10.1037/hea0000102

Cheval, B., Sarrazin, P., & Pelletier, L. (2014). Impulsive approach tendencies towards physical activity and sedentary behaviors, but not reflective intentions, prospectively predict non-exercise activity thermogenesis. *PLoS One, 9*(12), e115238. https://doi.org/10.1371/journal.pone.0115238
Cheval, B., Tipura, E., Burra, N., Frossard, J., Chanal, J., Orsholits, D., … Boisgontier, M. P. (2018). Avoiding sedentary behaviors requires more cortical resources than avoiding physical activity: An EEG study. *Neuropsychologia, 119*, 68–80. https://doi.org/10.1016/j.neuropsychologia.2018.07.029
Chevance, G., Héraud, N., Varray, A., & Boiché, J. (2017). Change in explicit and implicit motivation toward physical activity and sedentary behavior in pulmonary rehabilitation and associations with postrehabilitation behaviors. *Rehabilitation Psychology, 62*(2), 119–129. https://doi.org/10.1037/rep0000137
Conroy, D. E., & Berry, T. R. (2017). Automatic affective evaluations of physical activity. *Exercise and Sport Sciences Reviews, 45*(4), 230–237. https://doi.org/10.1249/JES.0000000000000120
Conroy, D. E., Hyde, A. L., Doerksen, S. E., & Ribeiro, N. F. (2010). Implicit attitudes and explicit motivation prospectively predict physical activity. *Annals of Behavioral Medicine, 39*(2), 112–118. https://doi.org/10.1007/s12160-010-9161-0
Corneille, O., & Hütter, M. (2020). Implicit? What do you mean? A comprehensive review of the delusive implicitness construct in attitude research. *Personality and Social Psychology Review, 24*(3), 212–232. https://doi.org/10.1177/1088868320911325
Corneille, O., Mierop, A., Stahl, C., & Hütter, M. (2019). Evidence suggestive of uncontrollable attitude acquisition replicates in an instructions-based evaluative conditioning paradigm: Implications for associative attitude acquisition. *Journal of Experimental Social Psychology, 85*, Article 103841. https://doi.org/10.1016/j.jesp.2019.103841
De Houwer, J. (2006). What are implicit measures and why are we using them. *The handbook of implicit cognition and addiction*, 11–28. https://doi.org/10.4135/9781412976237.n2
Deijen, J. B., Arwert, L. I., Witlox, J., & Drent, M. L. (2005). Differential effect sizes of growth hormone replacement on quality of life, well-being and health status in growth hormone deficient patients: A meta-analysis. *Health and Quality of Life Outcomes, 3*(1), 63. https://doi.org/10.1186/1477-7525-3-63
Dunton, G. F., Leventhal, A. M., Rothman, A. J., & Intille, S. S. (2018). Affective response during physical activity: Within-subject differences across phases of behavior change. *Health Psychology, 37*(10), 915–923. https://doi.org/10.1037/hea0000644
Ekkekakis, P. (2003). Pleasure and displeasure from the body: Perspectives from exercise. *Cognition & Emotion, 17*(2), 213–239. https://doi.org/10.1080/02699930302292
Ekkekakis, P., Hall, E. E., & Petruzzello, S. J. (2005). Some like it vigorous: Measuring individual differences in the preference for and tolerance of exercise intensity. *Journal of Sport & Exercise Psychology, 27*(3), 350–374. https://doi.org/10.1123/jsep.27.3.350
Ekkekakis, P., Parfitt, G., & Petruzzello, S. J. (2011). The pleasure and displeasure people feel when they exercise at different intensities. *Sports Medicine, 41*(8), 641–671. https://doi.org/10.2165/11590680-000000000-00000
Ekkekakis, P., Zenko, Z., Ladwig, M. A., Hartman, M. E., Williams, D. M., Rhodes, R. E., & Conner, M. (2018). In O. U. Press (Ed.), *Affective determinants of health behaviorAffect as a potential determinant of physical activity and exercise* (pp. 237–261). https://doi.org/10.1093/oso/9780190499037.003.0011
Ferdenzi, C., Delplanque, S., Mehu-Blantar, I., Cabral, K. M. D. P., Felicio, M. D., & Sander, D. (2015). The Geneva faces and voices (GEFAV) database. *Behavior Research Methods, 47*(4), 1110–1121. https://doi.org/10.3758/s13428-014-0545-0
Frossard, J., & Renaud, O. (2019). The correlation structure of mixed effects models with crossed random effects in controlled experiments. *Preprint at*. https://arxiv.org/abs/1903.10766.
Green, P., & MacLeod, C. J. (2016). Simr: an R package for power analysis of generalized linear mixed models by simulation. *Methods in Ecology and Evolution, 7*(4), 493–498. https://doi.org/10.1111/2041-210X.12504
Greenwald, A. G., McGhee, D. E., & Schwartz, J. L. (1998). Measuring individual differences in implicit cognition: The implicit association test. *Journal of Personality and Social Psychology, 74*(6), 1464–1480. https://doi.org/10.1037//0022-3514.74.6.1464
Hagura, N., Haggard, P., & Diedrichsen, J. (2017). Perceptual decisions are biased by the cost to act. *Elife, 6*, Article e18422. https://doi.org/10.7554/eLife.18422
Hardy, C. J., & Rejeski, W. J. (1989). Not what, but how one feels: The measurement of affect during exercise. *Journal of Sport & Exercise Psychology, 11*(3), 304–317. https://doi.org/10.1123/jsep.11.3.304
Hughes, S., Cummins, J., & Hussey, I. (2022). Effects on the Affect Misattribution Procedure are strongly moderated by influence awareness. *Behavior Research Methods*, 1–29. https://doi.org/10.3758/s13428-022-01879-4
Jennett, C., Cox, A. L., Cairns, P., Dhoparee, S., Epps, A., Tijs, T., & Walton, A. (2008). Measuring and defining the experience of immersion in games. *International Journal of Human-Computer Studies, 66*(9), 641–661. https://doi.org/10.1089/g4h.2019.0102
Kindermann, W., Schnabel, A., Schmitt, W., Biro, G., Cassens, J., & Weber, F. (1982). Catecholamines, growth hormone, cortisol, insulin, and sex hormones in anaerobic and aerobic exercise. *European Journal of Applied Physiology and Occupational Physiology, 49*(3), 389–399. https://doi.org/10.1007/BF00441300
Klein-Flügge, M. C., Kennerley, S. W., Friston, K., & Bestmann, S. (2016). Neural signatures of value comparison in human cingulate cortex during decisions requiring an effort-reward trade-off. *Journal of Neuroscience, 36*(39), 10002–10015. https://doi.org/10.1523/JNEUROSCI.0292-16.2016
Kohl, H. W., Craig, C. L., Lambert, E. V., Inoue, S., Alkandari, J. R.Leetongin, G., … (2012). The pandemic of physical inactivity: Global action for public health. *Lancet Physical Activity Series Working Group, 380*(9838), 294–305. https://doi.org/10.1016/S0140-6736(12)60898-8. The Lancet.
Krieglmeyer, R., & Deutsch, R. (2010). Comparing measures of approach-avoidance behaviour: The manikin task vs. two versions of the joystick task. *Cognition & Emotion, 24*(5), 810–828. https://doi.org/10.1080/02699930903047298
Krumhuber, E. G., Tamarit, L., Roesch, E. B., & Scherer, K. R. (2012). FACSGen 2.0 animation software: Generating three-dimensional FACS-valid facial expressions for emotion research. *Emotion, 12*(2), 351–363. https://doi.org/10.1037/a0026632
Kuznetsova, A., Brockhoff, P. B., & Christensen, R. H. B. (2015). lmerTest Package: tests in linear mixed effects models. *Journal of Statistical Software, 82*(13), 1–26. https://doi.org/10.18637/jss.v082.i13
Kwan, B. M., & Bryan, A. (2010). In-task and post-task affective response to exercise: Translating exercise intentions into behaviour. *British Journal of Health Psychology, 15*(1), 115–131. https://doi.org/10.1348/135910709X433267
Liao, Y., Chou, C.-P., Huh, J., Leventhal, A., & Dunton, G. (2017). Associations of affective responses during free-living physical activity and future physical activity levels: An ecological momentary assessment study. *International Journal of Behavioral Medicine, 24*(4), 513–519. https://doi.org/10.1007/s12529-016-9626-z
Lishner, D. A., Cooter, A. B., & Zald, D. H. (2008). Addressing measurement limitations in affective rating scales: Development of an empirical valence scale. *Cognition & Emotion, 22*(1), 180–192. https://doi.org/10.1080/02699930701319139
Magnan, R. E., Kwan, B. M., & Bryan, A. D. (2013). Effects of current physical activity on affective response to exercise: Physical and social–cognitive mechanisms. *Psychology and Health, 28*(4), 418–433. https://doi.org/10.1080/08870446.2012.733704
Maltagliati, S., Sarrazin, P., Fessler, L., LeBreton, M., & Cheval, B. (2022). Why people should run after positive affective experiences, not health benefits. *SportRxiv*. https://doi.org/10.51224/SRXIV.164
Mumenthaler, C., & Sander, D. (2012). Social appraisal influences recognition of emotions. *Journal of Personality and Social Psychology, 102*(6), 1118. https://doi.org/10.1037/a0026885
Mumenthaler, C., & Sander, D. (2015). Automatic integration of social information in emotion recognition. *Journal of Experimental Psychology: General, 144*(2), 392. https://doi.org/10.1037/xge0000059
Nash, J. C., & Varadhan, R. (2011). Unifying optimization algorithms to aid software system users: Optimx for R. *Journal of Statistical Software, 43*(9), 1–14. https://doi.org/10.18637/jss.v043.i09
Nelder, J. A., & Mead, R. (1965). A simplex method for function minimization. *The Computer Journal, 7*(4), 308–313. https://doi.org/10.1093/comjnl/7.4.308
Payne, B. K., Cheng, C. M., Govorun, O., & Stewart, B. D. (2005). An inkblot for attitudes: Affect misattribution as implicit measurement. *Journal of Personality and Social Psychology, 89*(3), 277–293. https://doi.org/10.1037/0022-3514.89.3.277
Payne, K., & Lundberg, K. (2014). The affect misattribution procedure: Ten years of evidence on reliability, validity, and mechanisms. *Social and Personality Psychology Compass, 8*(12), 672–686. https://doi.org/10.1111/spc3.12148
Pool, E., Brosch, T., Delplanque, S., & Sander, D. (2016). Attentional bias for positive emotional stimuli: A meta-analytic investigation. *Psychological Bulletin, 142*, 79–106. https://doi.org/10.1037/bul0000026
Powell, M. J. (2009). The BOBYQA algorithm for bound constrained optimization without derivatives. *Cambridge NA Report NA2009/06, University of Cambridge*, 26–46. Cambridge.
Preacher, K. J., Curran, P. J., & Bauer, D. J. (2006). Computational tools for probing interactions in multiple linear regression, multilevel modeling, and latent curve analysis. *Journal of Educational and Behavioral Statistics, 31*(4), 437–448. https://doi.org/10.3102/10769986031004437
Prévost, C., Pessiglione, M., Météreau, E., Cléry-Melin, M.-L., & Dreher, J.-C. (2010). Separate valuation subsystems for delay and effort decision costs. *Journal of Neuroscience, 30*(42), 14080–14090. https://doi.org/10.1523/JNEUROSCI.2752-10.2010
R Core Team. (2017). *R: A language and environment for statistical computing*. https://www.R-project.org/.
Rebar, A. L., Ram, N., & Conroy, D. E. (2015). Using the EZ-diffusion model to score a single-category implicit association test of physical activity. *Psychology of Sport and Exercise, 16*(3), 96–105. https://doi.org/10.1016/j.psychsport.2014.09.008
Rhodes, R. E., Cox, A., & Sayar, R. (2022). What predicts the physical activity intention–behavior gap? A systematic review. *Annals of Behavioral Medicine, 56*(1), 1–20. https://doi.org/10.1093/abm/kaab044
Rhodes, R. E., Fiala, B., & Conner, M. (2009). A review and meta-analysis of affective judgments and physical activity in adult populations. *Annals of Behavioral Medicine, 38*(3), 180–204. https://doi.org/10.1007/s12160-009-9147-y
Rhodes, R. E., & Kates, A. (2015). Can the affective response to exercise predict future motives and physical activity behavior? A systematic review of published evidence. *Annals of Behavioral Medicine, 49*(5), 715–731. https://doi.org/10.1007/s12160-015-9704-5
Rhodes, R. E., McEwan, D., & Rebar, A. L. (2019). Theories of physical activity behaviour change: A history and synthesis of approaches. *Psychology of Sport and Exercise, 42*, 100–109. https://doi.org/10.1016/j.psychsport.2018.11.010
Russell, J. A. (1980). A circumplex model of affect. *Journal of Personality and Social Psychology, 39*(6), 1161–1178. https://doi.org/10.1037/h0077714
Russell, J. A. (2009). Emotion, core affect, and psychological construction. *Cognition & Emotion, 23*(7), 1259–1283. https://doi.org/10.1080/02699930902809375
Saredakis, D., Szpak, A., Birckhead, B., Keage, H. A., Rizzo, A., & Loetscher, T. (2020). Factors associated with virtual reality sickness in head-mounted displays: A systematic review and meta-analysis. *Frontiers in Human Neuroscience, 14*, 96. https://doi.org/10.3389/fnhum.2020.00096

Scherer, K. R., Mortillaro, M., Rotondi, I., Sergi, I., & Trznadel, S. (2018). Appraisal-driven facial actions as building blocks for emotion inference. *Journal of Personality and Social Psychology, 114*(3), 358–379. https://doi.org/10.1037/pspa0000107

Schneider, M., Dunn, A., & Cooper, D. (2009). Affect, exercise, and physical activity among healthy adolescents. *Journal of Sport & Exercise Psychology, 31*(6), 706–723. https://doi.org/10.1123/jsep.31.6.706

Stahl, C., Haaf, J., & Corneille, O. (2016). Subliminal evaluative conditioning? Above-chance CS identification may be necessary and insufficient for attitude learning. *Journal of Experimental Psychology: General, 145*(9), 1107–1131. https://doi.org/10.1037/xge0000191

Stevens, C. J., Baldwin, A. S., Bryan, A. D., Conner, M., Rhodes, R. E., & Williams, D. M. (2020). Affective determinants of physical activity: A conceptual framework and narrative review. *Frontiers in Psychology, 11*, Article 568331. https://doi.org/10.3389/fpsyg.2020.568331

Timme, S., & Brand, R. (2020). Affect and exertion during incremental physical exercise: Examining changes using automated facial action analysis and experiential self-report. *PLoS One, 15*(2), Article e0228739. https://doi.org/10.1371/journal.pone.0228739

Williams, D. M., & Bohlen, L. C. (2019). Motivation for exercise: Reflective desire versus hedonic dreadM. H. Anshel, S. J. Petruzzello, & E. E. Labbé (Eds.). *APA Handbook of Sport and Exercise Psychology, 2*, 363–385. https://doi.org/10.1007/s12160-012-9362-9. American Psychological Association.

Williams, D. M., Dunsiger, S., Jennings, E. G., & Marcus, B. H. (2012). Does affective valence during and immediately following a 10-min walk predict concurrent and future physical activity? *Annals of Behavioral Medicine, 44*(1), 43–51. https://doi.org/10.1007/s12160-012-9362-9

Williams, D. M., & Evans, D. R. (2014). Current emotion research in health behavior science. *Emotion Review, 6*(3), 277–287. https://doi.org/10.1177/1754073914523052

Williams, D. M., Rhodes, R. E., & Conner, M. T. (2018). *Affective determinants of health behavior*. Oxford University Press. https://doi.org/10.1093/oso/9780190499037.001.0001

Williams, D. M., Rhodes, R. E., & Conner, M. T. (2019). Conceptualizing and intervening on affective determinants of health behaviour. *Psychology and Health, 34*(11), 1267–1281. https://doi.org/10.1080/08870446.2019.1675659

World Health Organization. (2019). *Global action plan on physical activity 2018-2030: More active people for a healthier world*. https://doi.org/10.1037/0000124-019. Retrieved from https://apps.who.int/iris/bitstream/handle/10665/272722/9789241514187-eng.pdf.

World Health Organization. (2020). *WHO guidelines on physical activity and sedentary behaviour*. Retrieved from https://www.who.int/publications/i/item/9789240015128.